Sensor-based smart hot-desking for improvement of office well-being

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ABSTRACT

Traditional hot-desking is a method of office resource management where a single office desk is shared by multiple employees at different times, instead of each one being assigned an individual desk. Utilising the desks in this manner can reduce the size of the office by up to 30% [?]. However there are numerous problems with the traditional approach, in particular with regards to desk personalisation, availability of preferred desks and the development of synergies between people doing similar work. The objective of this paper is to develop a smart hot-desking system that assigns temporary desks to employees in a way that takes into advantage personal preferences as well as spatial and temporal features in order to tackle the aforementioned issues and ultimately increase their well-being and productivity.

Sensors distributed in space measure the temperature, light and noise level in different areas of an office, in order for an algorithm to be able to determine an optimal desk for a specific employee, according to their prerecorded preferences. We performed an experiment with students in a university lab, with the majority of the users showing notable increase in their satisfaction with the working environment, as a result of the system allocating them desks. We discuss our experimental set-up, observations about the process and develop the concept further so that richer data can be fused in the future to inform even more meaningful desk allocation (e.g. calendar and to do lists).

This pilot study demonstrates the feasibility of combining real-time environmental sensor data and employees' feedback to produce a scalable desk allocation system.

CCS CONCEPTS

• **Information systems → Sensor networks**; • **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS

hot-desking, smart building

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1 INTRODUCTION

The world is becoming increasingly digital, which is leading to an increase in the volume and richness of available data, known as big data. One of the main sources of big data is the Internet of Things (IoT) [?], where both IT devices such as phones and traditionally non-IT objects like fridges or kettles include the ability to collect and transmit data [?], as well as occasionally being remotely activated.

One advantage of this is an increase in the amount of data being collected from cities, allowing the creation of more efficient, enjoyable and sustainable cities [?]. Cities that have distributed sensors generating big data in this way are known as smart cities. Despite the increasing amount of research into smart cities, substantially less research has been performed on the concept of smart buildings [?]. A smart building is one that incorporates sensors to collect data on its usage in order to decrease energy costs, increase connectivity and reduce its negative impact on the environment [?].

Data collected by sensors distributed in a smart building can also be used to better understand how efficiently people use the available space and to improve their well-being.

In this paper we present a system that can incorporate real-time environmental conditions and individual employees requirements

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for an ideal working environment, in order to allocate them an optimal place for work (sitting space at a desk) in a hot desking scenario. The intention of this system is to increase overall employee well-being and therefore productivity, whilst keeping the space saving advantages provided by traditional employee-run hot-desking approaches. If this system is successful it will allow offices to become more profitable (e.g. by reducing the size of rental space required), as well as potentially more sustainable (by optimising environmental conditions).

An employee's well-being depends on a number of different variables, the main ones being the interactions with their colleagues, their office environment and the work that they are doing. The premise of this work is that sensors distributed around the office can allow each employee to be assigned an available desk that's closest to their individual ideal office environment, increasing their well-being and therefore their productivity.

In addition to the direct effects that the proposed system will have on employee's well-being, there could be numerous other advantages, including a better understanding of how the noise, light and temperature are spatio-temporally distributed within the office space, which can aid decisions related to how the space is managed. More generally the experiments will produce data on the variation in people's desired office environment, as well as showing how the noise, light and temperature of the office affects individual happiness.

The sensing techniques covered in this work can be extended to the wider domain of smart buildings and Internet of Things (IoT) as well as potentially to the more general smart cities area of research.

We build on this work on modelling previously developed by Cooper et al. [?] and Maraslis et al. [?]. These papers create and extend an intelligent hot-desking model for a simulated environment, which uses as its input the occupancy of each desk and knowledge of the distribution of work-groups within the employee workforce. The optimal desk for each incoming employee is found by using a brute force algorithm that calculates the increase in the total productivity of the office for each possible desk assignment, assigning the desk with the largest increase in total productivity.

Productivity is assumed to increase when employees of the same work-group can interact with one another. One advantage of this productivity function is the incorporation of synergies, as when two employees from the same work-group are moved together they increase each-other's productivity.

The proposed system is inspired by this previous work, but the two approaches are complementary. In fact, the previous model optimises for social interactions, ignoring the environment, which is the opposite of the system presented in this paper. Moreover, while the previous model was designed to run within a simulated environment and there have been no physical experiments with it, the system being developed here needs to interact with a number of distributed sensors, as well as collecting and using data on the employees activities and feedback. Our system has a number of different inputs (environmental variables) and each employee has different preferences towards each one, which complicates the optimisation procedure, meaning that a more complicated objective function is needed.

To effectively include real time inputs from the environment in order to allocate personalised desks, a selection of environmental variables that have a significant impact on people's well-being need to be chosen. There is some research highlighting that the sensation of heat, is a key factor in a person's well-being and a person's response to heat can vary significantly depending on whether they have hypo-, hyper-, or normothermia [?].

Additional variables that research indicates have an impact on dissatisfaction and therefore employee productivity are: air quality, noise level and lighting [?]. It was decided to neglect air quality on the assumption that the air quality doesn't vary enough over an office, is hard to measure and that there is not much variation in employees preferences (they would all prefer cleaner air), however air quality could be explored further in later studies. Noise and light can vary more over an office as there are numerous sources of both. Furthermore people's response to noise and light level has a large variance, for example some people prefer to be surrounded by background noise while others desire as quiet an environment as possible to work [?]. This preference may also be depended upon the type of work conducted.

Due to the ease of measuring, the large effect they have on employees well-being and the ease that employees can state their desired value, our final selection of environmental variables for this pilot study were therefore: the ambient light, sound intensity (the upper envelope of the noise) and the ambient temperature.

The rest of the paper is organised as follows:

In the Methods section we 1) describe the hardware used to record the environmental variables of interest, and the surveys used to collect feedback on the employees' well-being. Then we 2) define a distance function between an individual's preferences about the environmental conditions and the sensor readings at a desk, to quantify the compatibility between a desk and an employee. Finally, we 3) use the distance function defined in 2) to develop a desk allocation algorithm to find the desk that most closely matches an employee's preferences.

In the Results section we 4) use the distance function defined in 2) to quantify the optimality of employee-led hot desking system, and we 5) validate whether the desk allocation algorithm developed in 3) is able to increase the satisfaction of employees through an experiment.

Finally, in the Conclusions we discuss the merits and limitations of the proposed approach, estimate the relevance of environmental conditions to the employees' satisfaction and outline the future next steps to generalise the proposed approach to include other important factors that need to be considered.

2 METHODS

This section introduces the different types of data and the methods used to collect them. First the employee's preferences about the environment are collected by an initial survey, then the collection of the environmental data is addressed. Once all the variables have been defined, the desk allocation algorithm is discussed. The method of evaluating the success of the experiment is next, before a brief overview of how the main program executes the desk allocation. Lastly the practical aspects of working with people are identified with a table of risks and a discussion of the potential privacy issues.

Variable	Name	Range	Resolution
Light	Ambient Light Bricklet	0 - 64,000 lux	0.01 lux
Noise	Sound Intensity Bricklet	0 - 4095 dB	1 dB
Heat	Temperature Bricklet	-40 - 125℃	0.1℃

Table 1: Final selection of environmental sensors.

2.1 Employees' Preferences Collection

In order to personalise the optimisation of the desk allocation, the system needs to know each employee's preferences towards the different environmental variables that are being used, namely: light, noise and temperature. The employees preferences are collected prior to the experiment starting by asking them to fill in a survey, which collects the following information:

- A unique ID/username, used to log into the system,
- The employees desired light, noise and temperature level (on a [0,1] scale),
- How important light, noise and temperature are to the employee (on a [0,1] scale),
- How long the employee stays in the office on average.

The survey was created using Survey Monkey [?], although other ways exist. The questions use a slider where possible so that the answers are returned as numerical values to allow them to be transformed into a set of tailored weights and preferences.

2.2 Environmental Data Acquisition

All of the hardware used in this system has come from Tinkerforge [?], which specialise in modular sensors.

The final selection of sensors that were chosen are shown in Figure ?? and key information on them is presented in Table ??. Each set of sensors (light, noise and heat) need to be combined with a central controller (Tinkerforge call a 'brick'), in order to collect the measurements and process them.

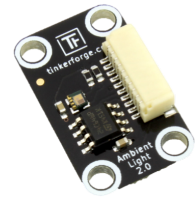
The central controller chosen for this system was the 'Master Brick' [?] made by Tinkerforge, which conveniently has four bricklet ports allowing full use of the sensors chosen. Figure ?? is a picture of the Master Brick, which is 4x4 cm.

Ideally the office will have a sensor of each type on each desk, in order that the system knows the exact environment of each desk. However it was decided to have a sensor hub for each of the three different areas of desks considered in this experiment. Using a single sensor hub for each area works as the differences between two neighbouring desks are negligible.

Each sensor hub is plugged directly into a laptop which turns the raw sensor input into a datafile and uploads it onto a shared folder, where it can be read in almost real time by the main computer that is running the program that the employees are interacting with.

2.3 Distance function

The system should allocate the desk with the environment (as measured by the environmental sensors) that is closest to the employee's given preferences. In order to do this, a distance function quantifying the closeness (or compatibility) of a given desk to a given employee's preferences needs to be defined. Once this function has been defined the problem becomes a simple optimisation to find the minimum of the function, given the free desks.



(a) Ambient Light Sensor

(b) Sound Intensity Sensor

(c) Temperature Sensor

Figure 1: The main items of hardware that were used to record the light, noise and temperature. All the items were purchased from Tinkerforge and these pictures are from their website [?].

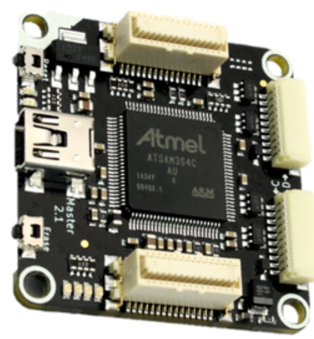
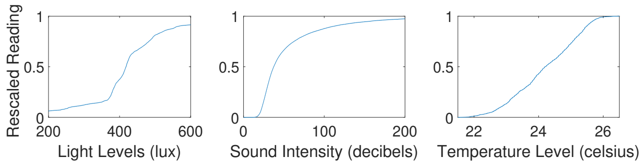


Figure 2: A picture of the master brick that is used to relay the sensor data to the main computer program. This image is from Tinkerforge's website [?].

The current environment at the ith desk can be represented as a vector containing the light, noise and temperature level, which will be called $\mathbf{c}_i$. The preferences of the jth employee can be represented as a vector containing their ideal level of the light, noise and temperature, which will be called $\mathbf{p}_j$. The distance function will therefore need to calculate the distance between these two vectors. There are a number of different ways that the distance can be found [?].

However this distance should also take into account the relevance of each of the three variables to a given employee, an information that was collected in the initial survey (Section ??). The importance that each of the three variables has to an employee is represented by a vector of weights, called $\mathbf{w}_j$, where each element



(a) Light Level **(b) Noise Level** **(c) Temperature Level**

Figure 3: The final empirical cumulative distribution functions for the pilot experiment that were generated using the full three weeks' worth of data, collected during the experiment.

is in the range [0, 1]. For example if they highly value a quiet environment, that's reasonably bright and are willing to compromise on the temperature there weight vector might be

$$\mathbf{w}_j = \begin{pmatrix} \text{Light} \\ \text{Noise} \\ \text{Temperature} \end{pmatrix} = \begin{pmatrix} 0.7 \\ 1 \\ 0.2 \end{pmatrix}$$

In order to incorporate these weights, it was decided to use the L1-norm distance function as a basis, inserting the weight of the kth variable ($w_{j,k}$) in the summation over the three variables (light, noise and temperature).

$$D\left(\mathbf{w}_j, \mathbf{p}_j, \mathbf{c}_i\right) = \sum_{k=1}^{3} w_{j,k}, \times \left|p_{j,k} - c_{i,k}\right|. \tag{1}$$

The objective function (Function **??**) assumes that the preferences and sensors readings are directly comparable, meaning that we can take the difference between the readings $\mathbf{c}_i$ and the preferences $\mathbf{p}_j$. However the preferences are defined on arbitrary units in the range [0, 1], while the three sensor readings are recorded in the raw units of lux, decibels and centigrade, and have different ranges and distributions.

The measurements can be made comparable to the preferences, by mapping them to the corresponding percentile and then rescaling them to the range [0, 1]. For example a temperature reading of 24.5℃ will be mapped to 0.5 as it is the median value of the temperature, as can be seen by Figure **??**C. We define the rescaled raw sensor readings as $R(\mathbf{c}_i)$, which replace $\mathbf{c}_i$ in function **??**.

In order to do this, a mapping from each variable to the percentiles / rescaled readings is needed. The mapping can be calculated from the raw data, by using the empirical cumulative distribution function (ecdf). The data can be collected prior to the experiment (i.e. during the control phase), and the mapping can be regularly improved by adding new data collected throughout the course of the experiment. Figure **??** shows the final empirical cumulative distribution functions for the pilot experiment, for each of the three variables being used. The ranges of the variables agree with common sense, for example the light level has a much higher variance than the temperature.

The desk allocation can be improved by using the mean value of each variable while the employee is in the office, as opposed to the current levels $\mathbf{c}_i$. In order to estimate what the future levels ($\mathbf{l}_i$) of each variable will be at the ith desk a regression can be performed on the data collected up until this point in the experiment.

When an employee enters the office, the mean value of each variable for each hour before the current time, is placed into a matrix of predictors. The responses are calculated by finding the mean of the remaining hours that the employee will be in the office for, using the average length of stay they supplied in the initial survey. These predictors and responses can then be used to calculate the coefficients of the regression, via a linear regression function.

Once the coefficients have been calculated, the mean of each variable for each hour recorded until the time that the new employee arrived is combined with the coefficients in order to produce an estimated mean level for each variable for the duration that the person is in the office for. The estimated future levels $\mathbf{l}_i$ can then be rescaled as before and takes the place of the current levels $\mathbf{c}_i$ in function **??**. The final resulting distance function is therefore:

$$D\left(\mathbf{w}_j, \mathbf{p}_j, \mathbf{l}_i\right) = \sum_{k=1}^{3} w_{j,k}, \times \left|p_{j,k} - R(l_{i,k})\right|. \tag{2}$$

2.4 Performance Evaluation

When the employees leave the office, they are asked to fill out a feedback survey. Upon the departure from the office, the program asked the participants to fill in a feedback survey before departing. The survey collects information on:

- How happy the employee was with their desk (on a [0,1] scale),
- which factors contributed most to that happiness (on a [0,1] scale) and
- what effect the people around the employee had on their happiness (on a [-1,1] scale),

The main purpose of this feedback survey is collect information on the employee's happiness, both in the control phase and during the allocation phase, to test if the allocation improves the employees happiness / well-being.

The secondary purpose is to identify other possible factors that affect employee's perception of a suitable desk, so that they can be included in future versions of the system.

For example, if an employee indicates on the feedback survey that they are unhappy and that the desk was too noisy, then their preferences towards noise should be reduced. If someone said the light level was too low / dim, then there preferences towards light should be increased, to decrease the likelihood that they'll be given a dim / low light level desk in the future.

The feedback survey (during the experiment, Figure **??**), asks for the employees happiness H (constrained to the range [0, 1]) and whether they believe that each of the three variables were 'High', 'Ok' or 'Low'. The direction of change in each of the variables is represented by the vector $\mathbf{\Delta}$, where each element is either -1 (Low), 0 (Ok) or 1 (High). The preferences (of the jth employee) $\mathbf{p}_j$, are constrained to the range [0, 1], as previously mentioned. It was therefore decided that the maximum change in the preferences M, when the happiness is at it's minimum of zero should be set to 0.2. The updated preferences $\mathbf{p'}_j$ are then defined as

$$\mathbf{p'}_j = \mathbf{p}_j - (\mathbf{\Delta} \times M \times (1 - H)). \tag{3}$$

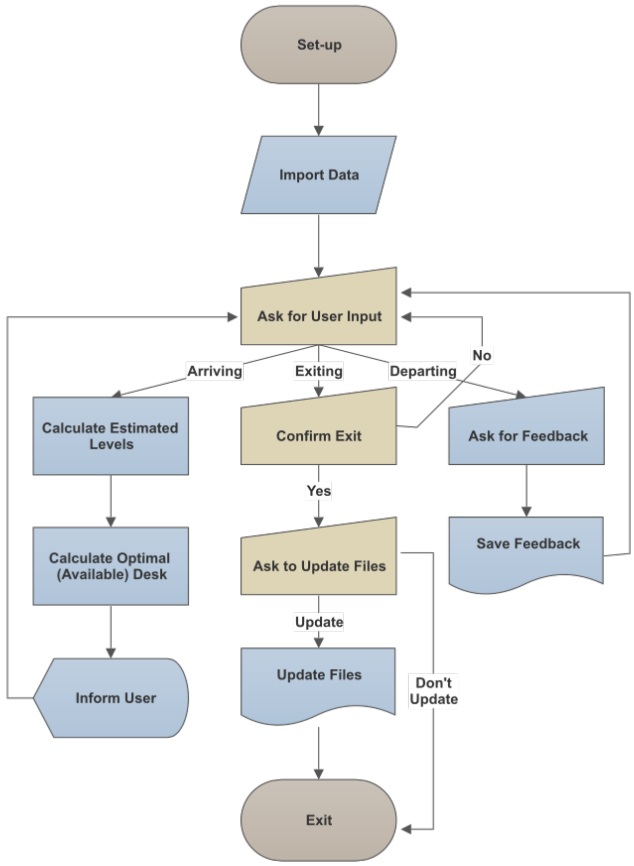


Figure 4: A simplified flowchart showing the key parts of the main computer program, in particular the main control loop.

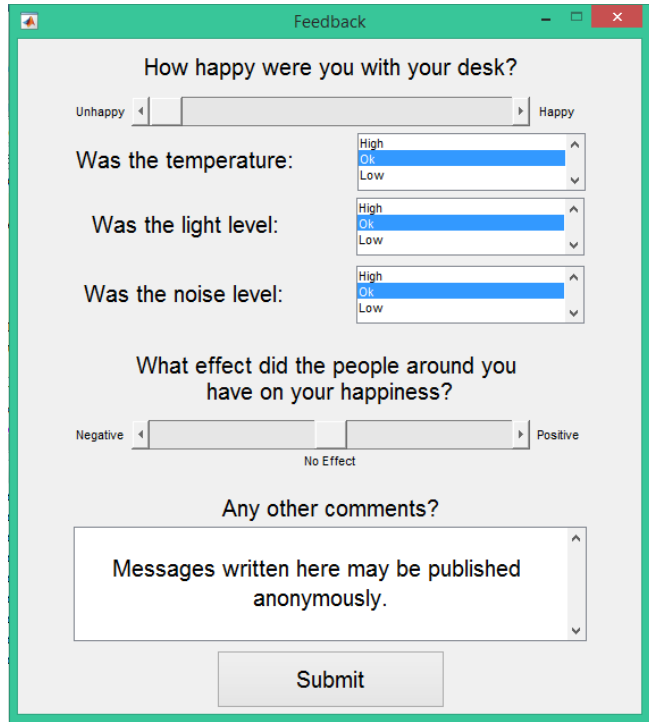


Figure 5: The feedback GUI that is displayed when the employee departs from the office. It's mainly used to assess their happiness with their desk, but also captures some key information about their feelings towards the temperature, light and noise, and how much of an effect the people around them had on their happiness.

Lastly the updated preferences need to be truncated back into the range [0, 1], by defining any value larger than one to be equal to one and any value lower than zero to be zero.

2.5 Desk allocation algorithm

A simplified overview of the algorithm used for the computer program running on the main computer is shown in Figure ??.

When an employee arrives, the program calculates the current levels of the sound, light and temperature for each area and estimated future levels are calculated by performing a regression on the current levels. The estimated future levels then need to be rescaled to match the employee's preferences. The rescaled readings for each area, the employees preferences and the employees weights are then used to find the optimal desk for the employee, i.e. the that minimises Eq. ??.

Once the optimal desk has been calculated, it is reported back to the employee via a simple pop-up box, and the program records them as being in that area.

When the employee is departing, the program updates them to be out of the office, before asking them to fill out the feedback survey described in Section ??.

The data (preferences, weights and average duration of stay) collected in the initial survey is not sensitive, hence privacy is not a significant issue. The feedback survey also asks for the employee's happiness, however it should be considered the happiness related to environment around the desk, rather than other conflicting factors, including overwork, therefore it has also not been considered sensitive.

At this instance of the study concerns about data privacy of participants led us to use a pseudo-anonymisation approach. Privacy is ensured by using an anonymous ID to link participants (users) to their data, rather than their name. The ID is unique but kept secret (issued as a password to be known only to the participant). The participants use this ID whenever they arrive or depart the office, hence it needs to be something that they can remember.

3 RESULTS

A pilot experiment involving students in a university computer lab was performed, in order to test the system.

The pilot experiment involved mostly fourth year MEng Engineering Mathematics students in the Engineering Mathematics Lab

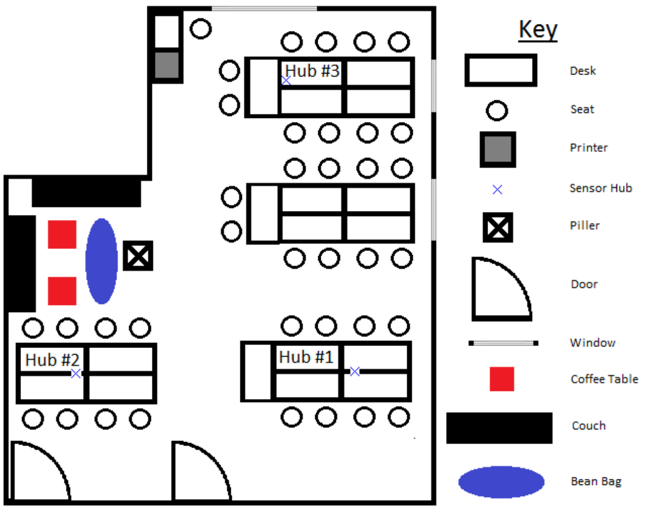
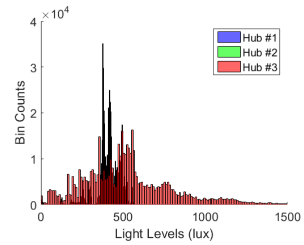
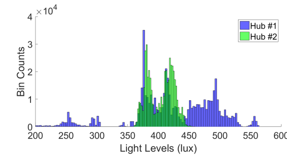


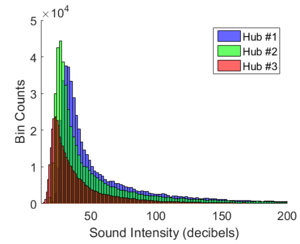
Figure 6: A map of the lab used for the pilot experiment, showing the location of the three hubs. Note the windows around Hub #3 and that the couch area near Hub #2 produces a lot of noise.



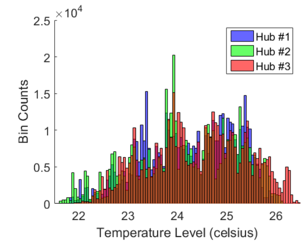
(a) Light Level



(b) Cleaned Light Level



(c) Noise Level



(d) Temperature Level

Figure 7: Histograms of the data collected at the different hubs over the course of three weeks. As the light sensor at Hub #3 appears to be broken, it has been removed in subfigure B.

(Figure **??**) at the University of Bristol. Three different areas of the lab were used for the experiment, which will be referred to as Hub #1, 2 and 3 for the rest of this chapter.

The experiment was stepped in nature, with two phases. The first phase lasted one week and it was a *control phase*, where the participants sat as they would normally and filled in the feedback survey (Section **??**). During this phase the system recorded data which it then used for rescaling and regression, as discussed in Section **??**. The second phase was the *allocation phase*: for one week the system allocated desks and the participants filled in the feedback survey, indicating their happiness.

Thirteen students signed up to the experiment, however the analysis that follows will mainly concentrate on seven of them. The additional students have been removed as they didn't use the system enough to allow for a meaningful analysis. It was decided that in order for a meaningful analysis to be performed only those students who used the system at least twice in the control and allocation phases would be included.

Analysis of sensors' readings. The raw sensor data from the entire three week period has been represented by a set of histograms, split by hub, as shown in Figure **??**, some useful summary information on the mean and standard deviation of the variables is displayed in Table **??**. The data has been smoothed by using a moving average filter, with a window of 100 data points corresponding to around a minute and a half long period of data collection.

Figure **??**A clearly shows that the light sensor at Hub #3 is faulty, as it has a much larger variation in values over the entire three week period that data was collected, this is further reinforced by the standard deviation shown in Table **??**. In order to better see the raw light levels it was therefore decided to remove that sensor, the result is shown in Figure **??**B.

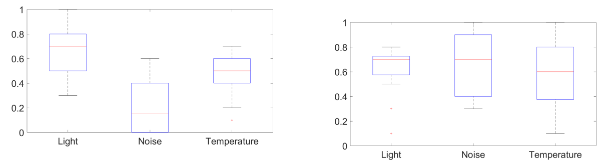
Hub Number	Variable	Mean	Standard Deviation
1	Light (lux)	417	80.6
	Temp (celsius)	24.2	1.21
	Noise (decibels)	62.2	49.2
2	Light (lux)	401	37.4
	Temp (celsius)	24.2	1.27
	Noise (decibels)	56.2	56.0
3	Light (lux)	532	275
	Temp (celsius)	24.4	1.25
	Noise (decibels)	42.5	34.0

Table 2: The mean and standard deviation of each of the variables, split by hub and rounded to 3 s.f. Note that the light sensor at Hub #3 has a much higher standard deviation.

As can be seen from the map in Figure **??**, the desks are very close together, which will naturally mean that the measured variables are similar, in particular temperature. The data agrees with this observation showing that Hub #1 and 2 both have a mean temperature of 24.2 degrees, with Hub #3 warmer by 0.2 degrees, on average. The values of the temperature will also naturally be similar in air-conditioned buildings.

There is a clear difference in the sound levels of the three hubs however, with Hub #3 being the quietest with a mean value of 42.5 dB (20 dB lower than Hub #1), as it is furthest from the couches. Unfortunately it is not possible to make a comment about the light level at Hub #3 due to the faulty sensor, although Hub #2 is dimmer than Hub #1 presumably as it is further from the windows.

Analysis of employees' preferences. In addition to the raw data recorded by the sensors, there is some interesting analysis that can



(a) Students preference distribution **(b) Students weight distribution**

Figure 8: Box and whisker plots showing the spread of all thirteen students preferences and weights towards each of the three variables.

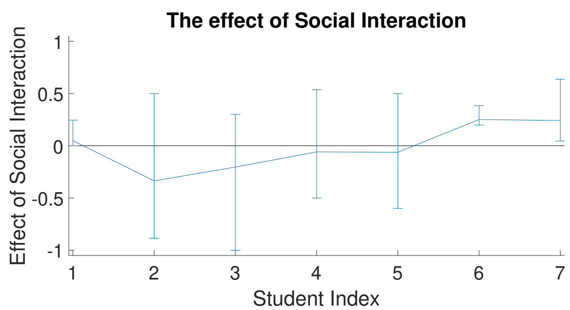


Figure 9: A Graph showing the variation in the effect of social interaction, per student. The data is mainly from the allocation phase, however it does include two days from the control phase.

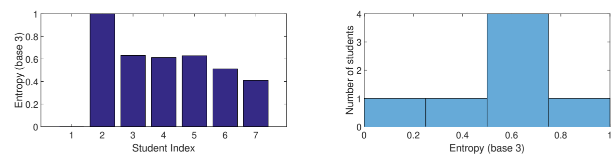
be performed on the results of the initial survey, using all thirteen students' answers. In particular looking at the range of values that they gave for the their preference (Figure **??**A) towards each of the variables as well as the corresponding weight (Figure **??**B).

The preferences clearly show that most of the participants like a bright and quiet room, with an average temperature level. While the weights are all predictably fairly high, with most people saying that everything is important, although noise has the highest weight of all. Meaning that we expect people to be assigned to Hub #3, as it has the lowest noise level. Which correlates with what occurred during the experiment.

Lastly participants thoughts on how the social interaction affected their happiness, which was collected as part of the feedback survey, has been plotted for each student in Figure **??**. Unfortunately this additional question was included after the control phase had started hence the data in Figure **??** is mostly from the allocation phase with only two days from the control phase.

The line shows the mean value, while the error bars show the maximum and minimum value that that each student gave. Interestingly most students said that the people around them decreased their happiness (negative social interaction). Although it is important to note the large range in values received, represented by the error-bars, as well as the small number of people involved, mean that it is hard to draw significant conclusions.

Occupancy Variations. As the system has minimal capacity to change the student's preferences and no mechanism to modify their weights, the desk allocation should be reasonably static, assuming that the different areas don't change significantly with respect to each other, during the experiment period.



(a) Bar chart **(b) Histogram**

Figure 10: The entropy in the desk assignment represented by a bar-chart and a histogram.

The variation in the desk assignment has been examined by calculating the entropy S in base 3, as there are three hubs.

$$S = -\sum_{i=1}^{3} p_i \log_3(p_i)$$

When the entropy is zero, the system always assigned the same hub to that student throughout the allocation phase. Conversely if the entropy is one that means that the system assigned each of the three hubs to the student with equal frequency.

The entropy for each student has been shown graphically with a bar chart and a histogram (Figure **??**A and B). Most people seem to have an entropy of around 0.6, representing being assigned to two hubs regularly, but never the third, showing that the system is fairly consistent.

Changes in Happiness. Validation has been performed by analysing the value that the students gave for their happiness in the control and allocation phases. The change in happiness between the control and allocation phases is shown in Figure **??**. The lines show the mean value for each student in each phase and the error bars show the maximum and minimum value that each student gave in the respective phase.

It appears that for most of the students, their mean value of happiness was higher during the allocation phase, than in the control phase. However the error bars are large, meaning that it's hard to tell whether the result is significant. It was therefore decided

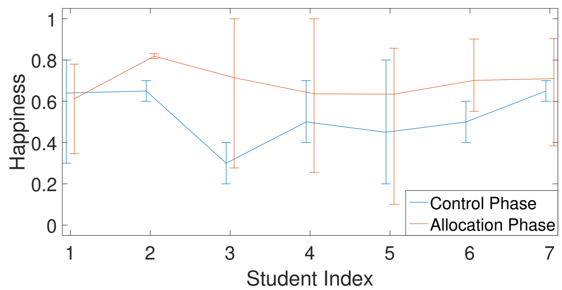


Figure 11: A graph showing how the value of happiness that each student gave varies between the control and the allocation phases.

to perform a hypothesis test on the data, looking at each student individually.

The bootstrap hypothesis testing [?] is a non-parametric method which involves combining all the data points in the control and allocation phases and drawing samples (with replacement) that are used to calculate the test statistic. The main advantage over other parametric hypothesis testing methods is that there is no assumption of the underlying distribution, in particular no assumption of normality.

The null hypothesis is that both samples (control and allocation) come from the same underlying distribution (meaning that there was no substantial change in the happiness for that individual). While the alternative hypothesis is that they come from different distributions and that the mean value during the allocation is significantly higher than the mean value during the control period (meaning that there was an improvement in the happiness). Setting the significance level as 5%, resulted in four (index: 2, 3, 5 and 6) of the seven students having a significant improvement in their happiness as a result of the desk allocation system, all the p-values are shown in Table **??** for completeness.

Student Index	P-value	
	Decimal	Percentage
1	0.599	59.9
2	**0.0241**	**2.40**
3	**0.0334**	**3.34**
4	0.185	18.5
5	**0.0443**	**4.43**
6	**0.0276**	**2.76**
7	0.328	32.8

Table 3: The p-values for the hypothesis that each student's happiness improved as a result of the allocation, shown to 3 s.f. The bold values are better than the 5% significance level.

4 CONCLUSIONS

Considering the difficulties due to the similarity between the hubs and that the lab is a complex environment with numerous external factors that could affect happiness, such as work pressure and people's personal health, creating a significant improvement in the majority of the students is considered a considerable success. In this section we outline the future next steps to generalise the proposed approach to include other important factors that need to be considered.

Participant Recommendations

Throughout both experiments that were performed as part of this project the people participating in them gave advice on how the system could be improved.

- Incorporate high peaks of noise, rather than just taking the average noise level.
- Take more note of the intra-hub differences.
- Being near a window is very important for some people.
- Cleanliness of the desk is a big factor in people's choice of desk.
- The condition of the equipment, desk and chair.
- Being in an area of high traffic, with a lot of people walking past, can be distracting.

The intra-hub differences can be solved by using more sensors or by using the existing sensors in a more intelligent way (discussed later in this section). Natural light does cause an area to be brighter which is within the current system, perhaps incorporating the wavelength of the light could allow the system to identify areas with more sunlight. Lastly an area of high traffic will cause the noise level to be increased, meaning if employees wish to avoid it they should specify quiet environments.

Improved User Interface

The graphical interaction aspects of this system are minimal. The main way that the interface could be improved is to allow the participants to dynamically update their preferences and weights, this will become more important as the system is used for longer periods of time, becoming essential if the system becomes permanent. A simple way to do this will be to have an online form, similar to the initial survey. Alternatively it could be incorporated into a mobile app.

If a mobile app is developed it could be used to improve the system in a number of key ways in addition to the ability to for employees to update their preferences and weights. Including recording environmental variables to supplement the system with additional data, informing the user which desk they've been allocated (by automatically communicating with the system when they enter the office) and collecting feedback information (if it is still required).

Incorporating Social Interaction

Previous work [?] solely considered the interaction of different work-groups in order to increase productivity, and describes how to incorporate these work groups into a simulated model. The main issue with adding social interaction to the system described in this report, apart from the difficulty in defining the work groups, is expanding the optimisation function (Eq. **??**) to include the effect of the work groups in addition to the environment, although the social and environmental aspects should complement each other meaning that solutions are likely to exist.

Another key issue highlighted by the experiments in this project, was the positive effect of sitting near people who you knew and are friendly with. As well as the converse negative effects of sitting near people who you did not know and perhaps disliked, or are very loud. The problem highlighted here is different as it shows the importance of informal interactions as opposed to purely professional ones.

Machine Learning

Machine learning algorithms could be used to improve the optimisation of the desks, in particular by learning what employee's preferences and weights should be, based on how they feel at the end of each day and the environment of the desk that they were in. Currently there is a minimal mechanism to update the employees preferences as discussed in Section **??**, but this can be substantially improved.

Potentially machine learning techniques could remove the need to ask for their preferences and weights before the system starts, which will allow for the use of less intuitive sensors that employees do not know their preferences towards, for example humidity or the carbon dioxide concentration. The main reason that this wasn't fully explored in this project was due to the short time period not providing enough data-points per person.

Scalability

One of the main limitations with the current system is that each area needs its own sensor hub, which means that the cost to deploy the system scales lineally with the size. Meaning that if the required system is double the size of the experiments detailed in this report (i.e. six areas rather than three), it would cost twice as much. As this is a linear relationship it may be acceptable, however it could be improved by dropping the assumption that each area is completely independent.

The data from a small number of sensor hubs can be used to generate a distribution over the entire office, using well defined laws governing how the temperature, light and noise flow around an enclosed space. The distribution calculation can use additional information, for example the number of employees in each area.

As the values of most environmental variables are stable, meaning that different areas do not change radically with respect to each other, the sensor hubs could be moved around to survey the entire office space and to ensure there are no anomalies, for example an air conditioning vent or a large dividing wall, which could change the way that the temperature, light or noise flow. The sensor hubs could be moved manually every day or once a week, or they could potentially be mounted onto small robots allowing them to move around the office continuously, transmitting the data wireless.

Another advantage of detailed mapping of the office is that the environment at each desk can be calculated. As opposed to assuming that each desk within an area monitored by a sensor hub is completely homologous and that nearby desks are identical (ignoring intra-hub differences). Which was mentioned by an employee as being an invalid assumption in some cases.

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